An Observing System Simulation Experiment for Hydros Radiometer-only Soil Moisture and Freeze-Thaw Products

(Invited Paper)

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Abstract— An important issue in the development of a dedicated space borne soil moisture sensor has been concern over the reliability of soil moisture retrievals in densely vegetated areas and the global extent over which retrievals will be possible. Errors in retrieved soil moisture can originate from a variety of sources within the measurement and retrieval process. In addition to instrument error, three key contributors to retrieval error are the masking of the soil microwave signal by vegetation, the interplay between nonlinear retrieval physics and the relatively poor spatial resolution of space borne sensors, and retrieval parameter uncertainty. Quantification of these errors requires the realistic specification of land surface soil moisture heterogeneity and spatial vegetation patterns. Since detailed soil moisture patterns are currently difficult to obtain from direct observations, an attractive alternative is the application of an observing system simulation experiment (OSSE) in which simulated land surface states are propagated through the sensor measurement and retrieval process to investigate and constrain expected levels of retrieval error. This manuscript describes results from an OSSE designed out to simulate the impact of land surface heterogeneity, instrument error, and retrieval parameter uncertainty on radiometer-only soil moisture products derived from the NASA ESSP Hydrosphere State (Hydros) mission.

I. INTRODUCTION

The Hydrosphere State (Hydros) mission has been selected by NASA for development under the Earth System Science Pathfinder (ESSP) program. The Hydros mission objective is to globally map dynamic patterns of surface soil moisture and freeze/thaw conditions using a combination of passive and active L-band microwave observations [1]. A key limitation for space borne soil moisture observations has been concern about their accuracy for areas of high biomass and land surface heterogeneity. Given the scale of Hydros radiometers observations (approximately 40 km) and the practical limitations of ground-based observations, such concerns are difficult to address using actual observations. A potential alternative is the use of the synthetic simulation experiments (OSSE's) where land surface heterogeneity is simulated using a distributed land surface model and used to generate high-resolution synthetic brightness temperature fields. These fields, in turns, can be: degraded to reflect sensors resolution and accuracy limitations, combined with realistically perturbed ancillary parameters, and then inverted back into a soil moisture product. Comparison of retrieved soil moisture fields with the original land surface model output provides a theoretical constraint on the impact of known retrieval uncertainties on the eventual accuracy of soil moisture products [2], [3]. Here, a Hydros-based OSSE is conducted during the 1994 growing season for two separate radiometer-based soil moisture retrieval algorithms.

II. APPROACH

The observing system simulation experiment (OSSE) described here is based on an existing methodology developed in [2] and [4]. It has four distinct components: (1) a land surface modeling component to predict surface geophysical states, (2) a forward microwave emission model to convert these geophysical states into microwave brightness temperature, (3) an orbit and sensor model to realistically degrade microwave brightness temperature fields based on the orbit and antennae characteristics of the Hydros mission, and (4) a retrieval model to invert simulated footprint-scale Hydros observations back into geophysical quantities (i.e. surface soil moisture). These components are discussed in the following subsections.

A. Land Surface Modeling

The 1-km surface (0-5 cm) soil moisture, 5-cm soil temperature field (T_{5cm}), and surface skin temperature fields (T_0) underlying the OSSE were derived from TOPmodel Land Atmosphere Transfer Scheme (TOPLATS) simulations over the 575,000 km^2 Red-Arkansas River Basin (Figure 1) during the May and June 1994 [5], [6].

B. Forward Microwave Emission Modeling

Forward microwave emission modeling followed the approached described in [4] and is briefly reviewed here. Model-generated θ, T_{5cm}, and T_0 were combined with ancillary data

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14. ABSTRACT

15. SUBJECT TERMS

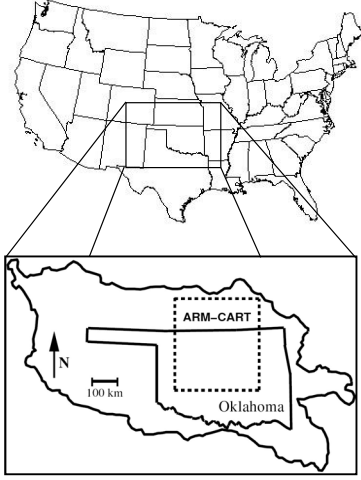| 16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT **UU**	18. NUMBER OF PAGES **4**	19a. NAME OF RESPONSIBLE PERSON
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Fig. 1. Location of OSSE domain (the 575,000 km^2 Red-Arkansas River Basin) in the United States Southern Great Plains.

in order to simulate 1-km H- and V-polarized microwave brightness temperature (T_B) via:

$$T_{Bp} = T_s(1 - r_p)\exp(-\tau_p/\cos(\phi)) + T_0(1 - \omega_p)[1 - \exp(-\tau_p/\cos(\phi))][1 + r_s p\exp(-\tau_p/\cos(\phi))] \quad (1)$$

where T_s is the effective soil temperature defined here as (T_0 + T_{5cm})/2, τ_p is the nadir optical depth, ϕ the look angle, and r_p the soil reflectivity. The subscript p refers to polarization (V or H). In turn, vegetation opacity is defined as

$$\tau = b_p W \quad (2)$$

The coefficient b_p varies with both vegetation type and W is the total columnar vegetation water content. Vegetation water content was prediction for the Red-Arkansas River basin using archived (1980 to 2000) 8-km AVHRR NDVI products and the regression relationship of [7]. As described in [4], a woody-vegetation correction factor was applied to convert the foliar W value derived via this regression relationship into the total columnar (i.e. truck, branches, and foliar) value required by (2).

Soil reflectivity (r_p) is calculated as

$$r_p = r_{sp}\exp(h) \quad (3)$$

where h is assumed to be 0.1 of the surface root-mean-squared height s and r_{sp} is the Fresnel reflectivity of the equivalent smooth surface. This reflectivity is derived from soil moisture via the Fresnel equation and the soil moisture mixing modeling of [8] given known values for percentage sand (S) and clay (C) soil contents. For inland water surfaces
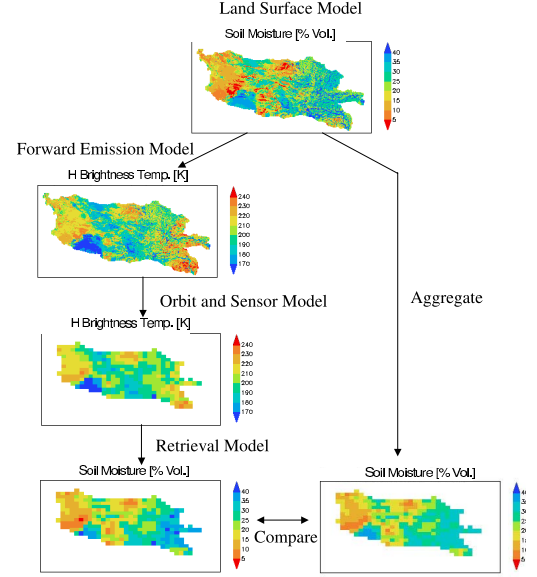
$$T_B = T_0(1 - r_s) \quad (4)$$

Fig. 2. Illustration of OSSE procedure using simulated soil moisture and brightness temperature imagery. Key components include the land surface modeling, microwave emission modeling, orbital and sensor modeling and soil moisture retrieval modeling.

where waves are neglected and r_{sp} is calculated via the Klein-Swift model.

Vegetation parameters b_p, ω_p, and s are assigned using a 1-km land cover classification and a lookup-table populated with typical literature values. S and C are taken from a soil classification map of the image and the USGS soil texture table. See Tables II and III in [4] for specific parameter values. Results presented here are based on a special case of scaling W by a factor of three in both the forward and inversion portions of the modeling. This was done to examine a sufficiently wide range of vegetation conditions and examine soil moisture retrieval performance under "worst-case" vegetation density and heterogeneity conditions.

C. Orbital and Sensor Model

A precise model of Hydros orbital and scanning characteristics was not used. Instead a Hydros overpass covering the entire OSSE domain was assumed every day at 6 am and 6 pm and footprint-scale T_B observations were computed by linear averaging of 1-km LSM T_B predictions within a 36-km fixed earth grid placed onto the OSSE domain. To simulate sensor noise, spatially independent Gaussian noise with a standard deviation of 1 K was added to each 36-km T_B retrieval. This was done independently for both radiometer polarizations and for each day of the simulation. Justification for a 1 K noise magnitude is given in [4].

D. Soil Moisture Retrieval Models

Two separate retrieval models were used to invert simulated footprint-scale T_B products back into soil moisture. The first approach is based on H-polarized T_B measurement and the approach of [9]. This single-polarization method neglects differences between soil and canopy temperatures by assuming $T_0 = T_s$. Given known 36-km ancillary values of h, ω_h, T_s, b_h, W, ϕ, S and C this allows (1) to be solved for r_{sp} which, in turn, is converted into a soil moisture estimate using the Fresnel equations and the soil-mixing model of [8]. The second approach is based on multi-polarized measurements of both T_{Bh} and T_{Bv} and the approach of [10]. Here, soil moisture and W are given initial estimates which are then interactively adjusted such that the difference between computed and observed dual-polarization brightness temperature is minimized. No a priori knowledge of W is required since it is simultaneously calculated along with soil moisture.

For both retrieval models, coarse-scale ancillary values of h, T_s, W, S, and C were obtained by aggregating 1-km fields used in the forward modeling component of the OSSE up to the 36-km footprint scale. In order to capture the impact of parameter error on soil moisture retrieval accuracy, synthetic noise was added to 36-km (i.e. footprint-scale) T_s and b_p values feed into the retrieval model. T_s and b_p noise was sampled from a mean-zero Gaussian distribution with a standard deviation of 1.5 K and 0.02, respectively, and assumed to be both spatially and temporally independent.

III. RESULTS

Figure 2 shows a schematic of the OSSE procedure along with imagery results for a single day of the simulation. Footprint-scale soil moisture products derived via the sequential application of the forward model, orbit and sensor model, and retrieval model(s) (left column) are compared with products derived via the simple linear aggregation of the original land surface model output (right column). Closer analysis of OSSE results from all days of the analysis reveals that spatial patterns in simulated retrieval errors are driven primarily by the distribution of vegetation within the domain. Figure 3b plots soil moisture RMSE in retrieval products (i.e. the left column of Figure 2) stratified by the mean vegetation water content (W) contained within individual 36-km pixels. Statistics are pooled values for all 36-km pixels in the Red-Arkansas River basin and all days of the OSSE. Significant errors are present in both algorithms for $W > 1.5$ kg m^{-2}. A large fraction of this RMS error is due with a positive bias in soil moisture retrievals (Figure 3a).

Sensitivity runs based on applying retrieval models at various scales indicate that this bias is primarily caused by aggregation efforts and the inability of coarse-scale (36 km) footprint-retrievals to capture fine-scale (1-km) land surface variability predicted by the LSM and high-resolution AVHRR imaging of the basin. Figure 4 illustrates this by comparing retrieval bias results for the application of the single-polarization algorithm to simulated 1-km T_s and T_{Bh} fields and the subsequent aggregation of 1-km soil moisture retrievals to
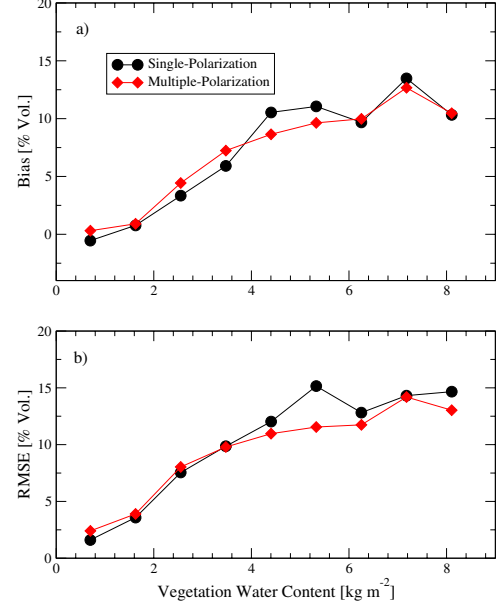

Fig. 3. Plots of retrieved 36-km soil moisture a) bias and b) RMSE stratified by 36-km vegetation water content values for both the single- and multi-polarization retrieval algorithm.
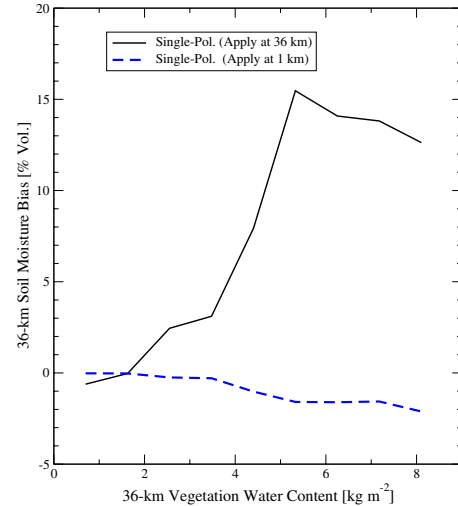

Fig. 4. Difference in soil moisture retrieval biases when applying the single-polarization algorithm to 1- (dashed line) and 36-km (solid line) geophysical fields.
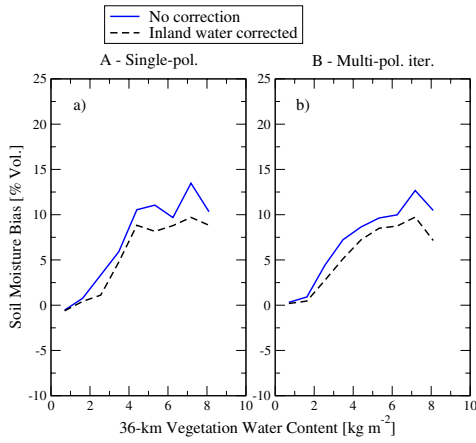
Fig. 5. For both retrieval algorithms, soil moisture retrieval biases, stratified by 36-km W levels, for the baseline retrieval case (solid line) and result derived after application of the inland water correction strategy

36km, to results for the baseline approach of applying retrieval models to 36-km T_s and T_{Bh} fields. The large positive bias observed at high W is eliminated by application of the retrieval model at a finer spatial resolution.

One distinct sub-set of aggregation errors are those associated with the contamination of footprint-scale observations by sub-footprint-scale areas of inland water. Actual 36-km T_B observations are based on a linear average of emission from both water and land surfaces

$$T_B = f_w T_{B,water} + (1 - f_w)T_{B,land} \qquad (5)$$

where f_w is the fraction of the footprint covered by water. This fraction can be estimated either from high-resolution VIS/IR imagery or the radar mapping capability of the Hydros sensor. Here, a separate f_w is determined for each 36-km pixel in the OSSE domain using a 1-km AVHRR land cover classification. Given knowledge of f_w, emission from the land surface can be estimated as

$$T_{B,land} = (T_B - f_w T_{B,water})/(1 - f_w) \qquad (6)$$

Assuming T_0 and f_w are known from ancillary sources, $T_{B,land}$ can be estimated using this expression and used in lieu of T_B observations to derive 36-km soil moisture products. Even though inland water constitutes a very small portion of the OSSE domain ($< 1\%$ by area), applying this correction leads to a significant reduction in soil moisture retrieval biases for both retrieval approaches (Figure 5).

IV. Conclusion

The observing system simulation experiment (OSSE) described here captures the influence of land surface heterogeneity, observation noise, inversion parameter uncertainty, and retrieval assumptions on the accuracy of radiometer-only Hydros soil moisture products. Examining these error sources in a controlled numerical setting provides an opportunity to assess eventual processing and retrieval strategies designed to mitigate their impact. Nevertheless, care should be taken when

equating error results presented here to accuracy expectations for actual Hydros soil moisture products. This particular OSSE provides a simplified representation of only a partial set of error sources within actual retrievals. Particular choices concerning the nature of represented error may impact the relative accuracy of various retrieval algorithms. In addition, while useful as a test-bed to study strategies for treating aggregation-based retrieval errors, results for the case of scaled-up vegetation density (3W) should be interpreted as a worst-case scenario of land surface heterogeneity and vegetation density encountered over only limited portions of the globe. Hydros soil moisture algorithms will undergo continued evolution and refinement prior to Hydros launch, based on a combination of OSSE results, further analyses, and data from ongoing airborne field campaigns. Given the generally large contribution of retrieval biases to overall RMSE (Figure 3), it may also be possible to improve the accuracy of retrieved soil moisture via calibration of retrieval model parameters.

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